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Conference Abstract

Convolutional Neural Networks for Phytoplankton identification and classification

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Abstract

Phytoplankton form the basis of the marine food web and are an indicator for the overall status of the marine ecosystem. Changes in this community may impact a wide range of species (Capuzzo et al. 2018) ranging from zooplankton and fish to seabirds and marine mammals. Efficient monitoring of the phytoplankton community is therefore essential (Edwards et al. 2002). Traditional monitoring techniques are highly time intensive and involve taxonomists identifying and counting numerous specimens under the light microscope. With the recent development of automated sampling devices, image analysis technologies and learning algorithms, the rate of counting and identification of phytoplankton can be increased significantly (Thyssen et al. 2015). The FlowCAM (Álvarez et al. 2013) is an imaging particle analysis system for the identification and classification of phytoplankton. Within the Belgian Lifewatch observatory, monthly phytoplankton samples are taken at nine stations in the Belgian part of the North Sea. These samples are run through the FlowCAM and each particle is photographed. Next, the particles are identified based on their morphology (and fluorescence) using state-of-the-art Convolutional Neural Networks (CNNs) for computer vision. This procedure requires learning sets of expert

validated images. The CNNs are specifically designed to take advantage of the two dimensional structure of these images by finding local patterns, being easier to train and having many fewer parameters than a fully connected network with the same number of hidden units.

In this work we present our approach to the use of CNNs for the identification and classification of phytoplankton, testing it on several benchmarks and comparing with previous classification techniques. The network architecture used is ResNet50 (He et al. 2016). The framework is fully written in Python using the TensorFlow (Abadi, M. et al. 2016) module for Deep Learning.

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Keywords

deep learning, phytoplankton, Convolutional Neural Networks, identification, machine learning, classification

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